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Research article

Impact of artificial intelligence adoption on students' academic performance in open and distance learning: A systematic literature review

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ABSTRACT

The role of artificial intelligence (AI) in education has been extensively studied, focusing on its ability to enhance learning and teaching processes. However, the precise impact of AI adoption on academic performance in open and distance learning (ODL) remains largely unexplored. This systematic literature review critically evaluates AI's impact on academic performance within ODL environments. Drawing from a curated selection of 64 papers from an initial pool of 700, spanning from 2017 to 2023 and sourced from Scopus, Google Scholar, and Web of Science, this study delves into the multifaceted role of AI in enhancing learning outcomes. The meta-analysis reveals a diverse methodological landscape: machine learning methods, employed in 29.69 % of the studies, stand out for their ability to predict academic achievement, which is matched in prevalence by classical statistical methods. Although less common at 3.13 %, hybrid methods are a burgeoning area of research, while a significant 40.63 % of works prioritise nonempirical methods, focusing on theoretical analysis and literature reviews. This investigation highlights the critical factors driving AI adoption in education and its tangible benefits for student performance. It identifies a crucial literature gap: the absence of a process-based framework designed to forecast AI's educational impacts with greater precision, especially across gender and regional lines. By proposing this framework, this study contributes to the academic discourse on AI in education. It underscores the urgent need for structured methodologies to navigate the challenges and opportunities of AI integration. This framework, aligned with UNESCO's 2030 educational objectives, promises to bridge educational divides, ensuring equitable access to quality education across diverse demographics. The findings advocate for future research to design, refine, and test such a framework, paving the way for more inclusive and effective educational technologies in ODL settings.

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1. Introduction

Artificial intelligence (AI) has reshaped the education landscape, driving unprecedented changes in teaching methodologies and student learning experiences. Through data-driven machine learning techniques, AI can optimise learning outcomes, streamline pedagogical processes, and tailor educational tools to individual needs [1]. The adoption of AI in education offers a promising pathway to personalised learning and improved academic performance. Particularly in the era of open and distance learning (ODL), understanding the impact of AI is crucial for educators, policymakers, and AI platform developers.

As suggested by Refs. [2–4], AI holds promising potential for democratising access to education. However, its full capabilities remain untapped, particularly within ODL systems. More extensive research and development are necessary to leverage AI's advantages in educational settings. A critical aspect of this endeavour is understanding the impact of AI on academic performance within these environments. Consequently, this study conducts a systematic review of the literature to identify key factors that influence the adoption of AI in ODL and explore its consequential effects on student academic performance.

The role of AI in education has been extensively studied, focusing on its ability to enhance learning and teaching processes [3,5]. However, the precise impact of AI adoption on academic performance in ODL remains largely unexplored. Several studies have identified success factors and challenges in implementing AI in educational settings but often lack a critical analysis of the direct influence of AI on academic performance, particularly within ODL systems [6–9]. Moreover, little research has focused on gender and regional disparities in the impact of AI on ODL performance, which presents a critical gap in the existing literature. Addressing this lacuna is essential for a more comprehensive understanding of AI's transformative potential in education. For instance, examining how cultural, socioeconomic, and infrastructural factors across different regions influence AI adoption can provide valuable insights into creating more inclusive educational technologies.

Furthermore, understanding gender disparities in AI's educational impact is crucial for promoting equity in AI-driven learning environments. Gender parity remains a significant challenge within the field of AI, including in educational contexts. The gender disparities identified within Canada's AI ecosystem underscore the need for targeted efforts to promote inclusivity and equal opportunity in AI education [10]. It is crucial to address these challenges and promote inclusivity in the field.

This study seeks to fill identified gaps in existing research through a systematic literature review. The primary focus is understanding how machine learning algorithms, particularly in the context of AI, can predict students' academic performance in ODL environments. This study also delves into potential gender and regional disparities that might moderate the effects of AI adoption to offer a comprehensive perspective. This review scrutinises key factors that influence AI adoption, evaluates the efficacy of machine learning algorithms for prediction, and identifies potential moderating variables such as gender and regional differences. Ultimately, the aim is to synthesise current research on AI's impact on academic outcomes in ODL settings, pinpoint the existing gaps, and propose avenues for more nuanced understanding.

Articles published between 2017 and 2023 from reputable databases were extensively reviewed to achieve this goal. The analysis highlighted key factors influencing AI adoption in ODL, gender differences in AI application usage, and the potential to predict AI adoption's impact on academic performance. This systematic review provides insights for various stakeholders, encouraging informed decisions that enhance AI-based platforms for diverse ODL students' needs. This endeavour is an essential step towards harnessing AI's potential to enhance learning outcomes in ODL. This research aims to promote gender equity and ensure that AI technologies effectively cater to students' educational requirements.

This study aimed to ascertain the effects of artificial intelligence adoption on student academic achievement in open and distance learning environments by employing a systematic literature review. This study systematically reviews the literature to assess the impact of AI adoption on academic performance in ODL, focusing on identifying key factors influencing AI integration and its effects on student outcomes. Unlike previous reviews, this study delves into gender and regional disparities in AI's educational impact, proposing a process-based framework tailored to diverse educational settings.

The structure of this paper is as follows: Section 2 presents a review of the relevant literature. Section 3 outlines the materials and methods utilised in the study, following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach. The findings and discussion are detailed in Section 4. Finally, Section 5 concludes the paper and offers pertinent recommendations. Having outlined AI's significance and potential in education, the existing body of research is now being explored. The following literature review systematically examines how AI technologies have been integrated into ODL systems and their impact on educational outcomes, drawing from various studies to build a comprehensive understanding.

2. Literature review

AI holds significant potential for ODL institutions. As [11] suggested, AI can enrich teaching and learning methodologies by offering personalised, adaptive learning experiences. However, it is also crucial to explore the associated challenges, such as integration complexities and the need for teacher training, to fully realise AI's benefits in educational settings. Notably, the structure, flexibility, and accessibility of the ODL have fostered increased participation of female students in IT and computer science studies [12].

Moreover, AI's integration into distance education significantly influences pedagogical strategies, mentoring approaches, and the content of education [13]. [14] demonstrated that blending AI with current e-learning platforms could offer all education stakeholders personalised, adaptive, and intelligent services. However, [15] cautioned that the full integration of AI into education is still unrealized, especially in developing an innovative educational ecosystem where schools, teachers, and students face numerous challenges posed by AI. [16] argued that AI and machine learning (ML), historically rooted in data management and development processes, have initiated a revolutionary trend across sectors, including education. They offer a personalised approach, enhancing learning experiences by tailoring platforms and applications to individual student needs. This shift towards AI in education has led to extensive research, solidifying it as an evolving field within the sector.

Advanced countries have shown a keen interest in the role of AI in higher education, resulting in a rich body of literature. Some of these researches have examined AI's potential to personalise learning, enhance student engagement, and streamline administrative processes. However, this interest is not uniformly distributed, with significant research gaps in developing regions. Addressing these disparities is crucial for ensuring that AI benefits are equitably distributed across different educational contexts. The promise of AI and ML technologies lies in their potential to enhance education by promoting student proficiency, easing group collaboration, and facilitating access to academic resources. As AI tools continue to gain prominence, their potential for enhancing learning outcomes in educational settings is increasingly recognised. The adoption of AI in education has significantly expanded in recent years. The integration of AI into ODL is poised to transform students' learning experiences and potentially improve their academic performance.

Guided by an extensive literature review, this study seeks to address the following research questions.

I. **Determinants of AI Integration:** What factors are pivotal for successfully integrating AI within ODL environments?
II. **The Influence of AI on Academic Outcomes:** How significantly does AI affect students' academic performance in ODL settings?
III. **Predicting Academic Performance:** Can the determinants be used through machine learning to predict students' academic outcomes accurately?
IV. **Role of Moderating Factors:** How do aspects such as gender and regional differences moderate the impacts of AI on academic performance in ODL?

This systematic review meticulously examines the available literature to uncover key drivers of AI adoption in the ODL, assess their influence on academic performance, evaluate the predictive accuracy of these determinants through the support vector machine (SVM) approach, and understand the modulatory effects of gender and regional variances on AI efficacy. The literature is categorised as follows for a thorough review.

I. **Elements Catalysing AI Implementation in ODL:** Identifying Primary Motivators for AI Incorporation in ODL.
II. **Impact of AI Adoption on Academic Results in ODL:** Examining the Effects of AI on Students' Academic Achievements in ODL Settings.
III. **Predictive utility of machine learning:** Analysing the predictive capabilities of the identified determinants for academic outcomes using machine learning was considered.
IV. **Moderating Elements Evaluation:** Assessing the influence of gender and geographical disparities on the effectiveness of AI adoption in ODL.

2.1. Elements catalysing AI implementation in ODL

Research Question 1: Identifying the determinants of AI integration within ODL environments: What elements contribute to the successful implementation of AI in ODL settings?

An exhaustive review of the existing body of literature was conducted to identify and understand the essential variables catalysing AI incorporation within the ODL context. This endeavour yielded several noteworthy factors serving as key propellants for this technological advancement. The leading technology acceptance theories, such as the Technology Acceptance Model (TAM), focus on ease of use and usefulness [17]. At the same time, information systems success (D&M model) emphasises system quality and user satisfaction [18]. The unified theory of acceptance and use of technology (UTAUT), which considers a broader framework that includes social influence [19], was reviewed. These theories offer a nuanced understanding of the factors affecting AI adoption in ODL settings.

Recent studies underscore the importance of personalised learning in ODL contexts, showing that academic outcomes improve and student engagement increases when AI is used to tailor educational experiences [2]. Additionally, learning analytics help refine instructional methods [20]. These findings are supported by Ref. [21], which highlights that addressing social and computer anxiety is essential for enhancing student engagement in e-learning environments. By reducing these anxieties, students experience greater motivation and satisfaction, leading to an overall improvement in their learning experience.

In addition, [22] highlighted that self-reported familiarity with AI correlates with increased approval of AI applications. This suggests that enhancing user experience and providing real-time feedback can positively influence attitudes toward AI adoption. Factors such as perceived ease of use, perceived usefulness, and attitude significantly influence students' ODL. The study also highlights the mediating roles of utilitarian and hedonic values in this acceptance process [23]. From an institutional perspective, readiness for AI, adaptability of business processes, and leadership emerge as critical factors in facilitating AI adoption [24]. At the individual level, perceived usefulness, performance expectancy, attitudes, trust, and effort expectancy govern AI technology's intention and actual usage [25]. Consequently, understanding these variables provides crucial insights into the broader narrative of AI incorporation within ODL contexts.

Although some commonalities exist, the factors prompting AI adoption in ODL and traditional educational settings differ significantly. The factors driving AI adoption in ODL and traditional settings vary, with AI enhancing ODL through governance, decision-making, and teaching [21,24–26]. [26] highlights AI's role in personalised learning and educational efficiency. Reinforced by the TAM of [27], these factors include acceptance, technology access, motivation, self-efficacy, perceived ease of use and usefulness, enjoyment, and social influence. Within ODL structures, the successful amalgamation of AI technology largely depends on its alignment with institutional goals, values, and necessities. [24] added that significant aspects of AI's successful integration include its relative advantages over traditional methods, the institution's preparedness for AI, and the flexibility of processes to accommodate AI.

Emotional aspects of learning, such as learning-related anxiety and readiness for online collaboration, play a crucial role in AI adoption. The impact of AI systems on knowledge acquisition and the enhancement of online interactions are considered integral to AI incorporation [3,5,6]. In contrast, adopting AI in conventional learning environments is influenced by different factors, including performance anticipation, attitudes toward AI, trust in the system, effort expectancy, and perceived relevance of the technology [25]. The facilitation of AI adoption in ODL environments primarily relies on aligning AI systems with institutional and student requirements and adaptability to technological advancements. However, the adoption of AI within traditional educational settings is influenced primarily by these systems' perceived utility and user-friendliness.

2.2. Consequences of AI adoption on academic outcomes in ODL: investigating the repercussions of AI implementation on the academic performance of ODL students

Research Question 2: Assessing the influence of AI on students' academic outcomes within ODL settings: To what extent does the incorporation of AI impact the academic performance of students engaging in ODL?

The research question above leads us to examine the factors impacting students' academic performance within ODL, particularly in light of AI implementation. The wealth of literature signifies a substantial positive correlation between the application of AI within ODL scenarios and improvements in students' academic outcomes. Specifically, when AI systems are employed to personalise learning experiences and provide timely, relevant feedback, a substantial improvement in student performance is noted [28].

AI-driven tutoring systems improve learning outcomes by offering personalised instruction [29]. A review by Ref. [30] highlights Moodle as the preferred LMS for AI integration, commonly used for assessing student performance. Together, these studies confirm that AI enhances academic achievement. These investigations underline key mechanisms through which AI adoption can lead to better academic performance. AI integration has brought transformative effects across various sectors and practices, including:

I. Augmentation of learning outcomes
II. Amplification of student engagement
III. Provision of improved decision making process [31].
IV. Improved resource optimization [32].

These results underscore the game-changing potential of AI within the ODL domain as well, revamping the learning process and propelling academic success. The determinants propelling AI adoption within ODL settings can also positively influence academic performance. There are several specific mechanisms through which these factors can impact academic outcomes in the ODL.

I. AI performance prediction models have shown considerable accuracy in gauging student academic performance in online higher education. For example, these models can identify students at risk of underperforming by analysing patterns in their engagement and learning behaviours. Such predictive capabilities enable educators to implement targeted interventions, such as personalised tutoring or additional resources, which can significantly improve student outcomes. Moreover, these models have the potential to refine educational strategies by providing data-driven insights into the factors that most influence academic success [33,34]. This predictive ability can be leveraged to identify at-risk students and create student-centric learning trajectories.
II. By merging AI with learning analytics, student learning in online engineering courses can be significantly improved [33]. By providing real-time, ongoing feedback, the quality of student learning is enhanced.
III. AI-enabled prediction models can forecast academic achievement in online education, enabling instructors to curate and deliver more effective learning experiences [35,36]. This, in turn, allows instructors to adapt their methods to meet individual student needs.
IV. Machine learning algorithms can track students' academic progress and notify instructors about students at risk of performing poorly in a course [34]. Timely interventions can be implemented to enhance student performance.
V. Machine learning algorithms can achieve high predictive accuracy by estimating student enrollment, college admission, dropout rates, and the risk of failure and withdrawal in online courses [36]. This empowers institutions to support student success better and make informed decisions.
VI. The merger of AI and learning analytics can aid instructors in making data-driven decisions to facilitate student-centric learning and enhance the knowledge-creation processes of student cohorts [33].

The impetus behind AI adoption within ODLs has the potential to positively influence academic performance by providing precise predictions and monitoring of student performance, enhancing student learning, identifying students at risk of poor performance, and facilitating data-driven decision-making by instructors. These results underline the immense potential of AI within ODL to augment educational outcomes and curate a more effective, personalised learning environment for students.

Nonetheless, implementing AI within ODLs is not without potential drawbacks and challenges. Existing research points out the potential disadvantages of AI implementation within ODLs, particularly regarding students' academic performance [21]. A critical observation is that the success of AI heavily relies on students' perceptions of it, indicating a need to alleviate AI-associated anxiety to achieve optimal results.

Both students and educators have expressed concerns about the growing role of AI in education, including fears that an overreliance on technology may limit opportunities for exploration and hinder self-guided learning [6,37]. Misconceptions about AI often exacerbate these apprehensions and can contribute to technology-induced anxiety, impeding its effective adoption. Thus, while AI holds promise for enhancing educational support, addressing these concerns is necessary to ensure that it augments rather than restricts the learning experience.

A more nuanced exploration is essential to fully understand the impact of AI on students' academic performance in ODL. While AI promises to improve learning outcomes and enable personalised education, it also raises concerns such as overstandardisation and increased anxiety. Addressing these complexities requires the development of a robust framework that can predict AI's effects on academic performance and navigate challenges. This framework should strike a balance between AI's benefits and potential drawbacks, serving as an essential tool for the effective and responsible integration of AI in ODL environments.

2.3. Foreseeing academic outcomes utilising machine learning: understanding the predictive power of the identified elements on academic performance using the machine learning method

Research Question 3: Employing a machine learning method for predicting academic performance: Can these determinants be utilised to anticipate students' academic outcomes via a machine learning approach?

An expansive body of literature has delved into the application of SVM for predicting student outcomes in ODL settings. For instance Ref. [38], underscored the utility of machine learning methodologies, including SVM, in predicting student dropout based on demographic factors, academic records, and engagement levels. [39] further reinforced the efficacy of SVM in predicting student performance when trained on parameters such as historical academic records and behavioural tendencies. Significant insights were also provided by Ref. [40], who found SVM particularly effective in predicting engagement levels by analysing student interactions in online learning environments. This body of work strongly suggests the potential of SVM as a tool to increase student engagement and ameliorate overall learning outcomes.

Prior studies on non-AI variables [41,42] have derived some results on the influence of ICT tools on learning outcomes with minimal results. However, advancements in AI-based performance prediction models have been notably evident in online education. Research by Refs. [33,35,43,44] exemplifies the application of these models in online higher education. These studies highlight the use of AI to predict and track student performance by utilising learning data and machine learning techniques. Additionally, the scope of AI extends to areas beyond student learning, as demonstrated by studies such as [45], which introduce models to evaluate instructor performance.

This intertwining of AI and learning analytics has fostered innovative pedagogical approaches, providing educators with valuable data to facilitate student-focused learning and enhance the quality of online education [33]. In particular, machine learning, a subset of AI, and evolutionary computation have been harnessed to develop performance prediction models, contributing to improved prediction accuracy [35,46,47]. AI algorithms, notably machine learning, play a pivotal role in constructing performance prediction models using student learning data to predict and monitor academic progress [33,35,48]. However, the efficacy of AI algorithms in these models can vary based on the specific algorithm implemented.

The findings revealed that machine learning algorithms are extensively used, with the random forest algorithm demonstrating notable accuracy [49]. Among these algorithms, the SVM approach has shown promising results, with [49] finding it more accurate than other machine learning algorithms in predicting student performance. AI algorithms thus offer substantial benefits in online education, facilitating the early identification of at-risk students, enabling preventative measures, providing personalised recommendations, and offering valuable data for informed decision-making [25,33].

In summary, AI performance prediction models present considerable advantages in online education, accurately predicting student performance and providing educators with the necessary data for informed decision-making. The selection of the most effective AI algorithm, such as SVM, is thus integral to precise performance prediction.

2.4. Moderating elements: gender and geographic differences

Research Question 4: Recognising the role of moderating aspects such as gender and regional variances in the impact of AI: Do factors such as gender and geographical disparities moderate the effects of AI implementation on students' academic performance within the ODL?

It is crucial to examine moderating factors, specifically gender and regional differences, to understand the impact of AI on students' academic performance in the ODL. Research has indicated noticeable disparities in the attitudes and usage patterns of AI-enhanced educational tools between male and female students. This factor influences the impact of AI on ODL [50]. Moreover [51], raised concerns about gender biases unwittingly embedded within AI systems during the developmental process. These biases may subtly reinforce existing stereotypes about women and, in turn, influence how both genders interact with AI systems.

Regional differences, such as the availability of technology infrastructure and cultural attitudes towards technology, also affect AI effectiveness in education [52]. This aspect is essential in ODL contexts, which heavily rely on technology and its accessibility. [53] highlighted the significant implications of the growing presence of AI, including the potential to exacerbate the digital divide among genders. Over 66 % of the world's 796 million illiterate individuals are women, with the majority of the world's 2.9 billion people without internet access also being women. This inequity obstructs women's progress across economic, social, and educational realms, emphasising the need to consider gender differences when adopting AI-based applications in ODL settings.

While AI promises to enhance ODL outcomes, it is essential to account for personal and regional differences that impact its effectiveness. Future research should continue to scrutinise these differences and strategies to maximise the benefits of AI for ODL. Specifically, further investigations of moderating factors, such as gender and regional disparities, on the impact of AI on students' academic performance in the ODL are needed.

This study serves as a foundation for further exploration into the determinants of AI adoption and its implications for academic performance in ODL environments. It elucidates the key drivers behind AI adoption, the efficacy of SVM as a predictive model, and the importance of well-structured process frameworks. Although AI holds significant promise for enhancing learning outcomes, boosting student engagement, and providing tailored learning experiences, it is equally important to acknowledge its possible adverse effects on student academic performance. This balanced view highlights the critical importance of developing a comprehensive process framework. Such a framework would help forecast the impact of AI integration on students' academic advancement, especially in the context of ODL.

The findings suggest that AI adoption can significantly influence educational outcomes in ODL settings. However, the outcomes depend largely on the context, including factors such as individual student characteristics, the learning environment, and the specific type of AI technology implemented. As such, further research is necessary to fully comprehend these complexities and develop effective strategies for AI integration in ODL environments. Overall, it is essential to continue advancing research in this domain to unlock the full potential of AI in enhancing ODL outcomes. This systematic literature review contributes to this objective by providing a comprehensive overview of the current state of research and highlighting critical areas for future investigations.

2.5. Taxonomy of AI techniques and approaches

Researchers have employed a broad spectrum of methodologies within AI in education, focusing on its ability to enhance learning and teaching processes, especially in ODL environments. The diversity of these approaches, ranging from empirical to theoretical analyses, underscores the multifaceted nature of AI's application in educational settings. Understanding these various methodologies is crucial for understanding the comprehensive landscape of AI in education. This section introduces a taxonomy of the techniques and approaches identified in the systematic literature review, aiming to categorise and elucidate the methodologies paving the way for the role of AI in enhancing educational outcomes. The methodologies applied in AI in education can be broadly categorised into four distinct groups, each contributing uniquely to the field. Table 1 organises the methodologies into four main categories, detailing their application in education and the prevalence of their use in the reviewed studies:

This taxonomy reveals notable trends in the application of AI in educational research. For instance, the growing interest in machine learning methods reflects the field's shift towards more sophisticated predictive analytics. Moreover, the reliance on nonempirical methods highlights the need to conceptualise AI's theoretical underpinnings and potential educational impacts. Together, these methodologies contribute to a richer, more nuanced understanding of AI's role in educational settings, from enhancing personalised learning experiences to predicting academic outcomes.

The taxonomy laid out above serves as crucial groundwork for comprehensively understanding the application and impact of AI in education. As the transition to a comparative study of related works occurs, this classification provides a lens through which critical analysis and comparison of the diverse methodologies employed in the field can be conducted. By doing so, the aim is to identify gaps, opportunities, and emerging trends in AI research within educational settings, further contributing to the academic discourse on leveraging AI to improve teaching and learning in ODL environments. The following section on the comparative study in related work will build upon this taxonomy, delving into a detailed analysis of how these methodologies are applied across different studies to address the challenges and opportunities of AI in education.

A comprehensive taxonomy and comparative summary table have been developed. Table 2 presents a succinct overview of the diverse AI techniques and approaches identified in the literature review. This summary encapsulates each approach's key attributes, strengths, and limitations, enriching the Related Work section with a clear and comparative perspective.

2.6. Comparative study in related work

Table 3 provides a snapshot of selected studies on how AI has been investigated within the context of education, highlighting diverse methodologies, from theoretical discussions to machine learning applications and a variety of focus areas, from performance

Table 1
Taxonomy of AI methodologies in education.

Category	Application	Number of Articles	Percentage of Studies Utilising
Machine Learning Methods	Predictive modelling of academic performance, student engagement, and dropout risk identification.	19	29.69 %
Classical Statistical Methods	Fundamental statistical analyses for trends, correlations, and predictions in academic data.	17	26.56 %
Hybrid Methods	Combining AI and statistical techniques for enhanced prediction accuracy or comprehensive insights.	2	3.13 %
Nonempirical Methods	Theoretical analysis, literature reviews, conceptual frameworks on AI's role in education.	26	40.63 %

Table 2
Comparative summary of AI techniques and approaches in related work.

AI Technique/ Approach	Description	Application in ODL	Comparative Advantages	Limitations
Machine Learning Methods	Algorithms that learn from data to make predictions or decisions.	It is used to predict student performance and personalise content.	The methods provide high predictive accuracy and adaptability to new data.	It can require large datasets and may be complex to interpret.
Classical Statistical Methods	Traditional methods for statistical analysis.	Analysing educational data reveals trends and correlations, offering insights into teaching methods' effects on student outcomes.	Well-established and more straightforward to interpret.	It may not capture complex patterns as effectively as machine learning.
Hybrid Methods	This is a combination of AI and statistical techniques.	It provides enhanced prediction accuracy and comprehensive insights.	The methods leverage the strengths of both AI and traditional statistics.	It can be more complex to implement and interpret.
Nonempirical Methods	The methods provide theoretical analysis and literature reviews.	It is used in developing conceptual frameworks on AI's role in education.	No reliance on empirical data can propose new theories.	Lack of empirical validation may not account for practical considerations.

Table 3
Comparative summary of related works with references.

Author(s)	Year	Focus Area	Methodology	Key Findings	Reference
Ouyang et al.	2023	AI Performance Prediction in Engineering Education	Machine Learning	Utilised AI to predict and improve student learning in online engineering courses.	[33]
Aggarwal Sharma & Saxena	2023	AI Implementation in ODL	Review	The study emphasised personalised learning and educational efficiency as key benefits of integrating AI into Open and Distance Learning (ODL).	[26]
Jiao et al.	2022	Predictive Utility of Machine Learning	Empirical Study	The study highlighted the forecasting ability of AI models in the context of online education.	[35]
Kurup & Gupta	2022	AI Implementation in ODL	Review	The research underscored that institutional readiness and leadership are critical factors for successfully adopting AI.	[24]
Wang, Liu, & Tu	2021	AI Adoption in Higher Education	Survey Analysis	Factors affecting AI adoption include technological access, motivation, and perceived ease of use.	[1]
Chen et al.	2020	AI's Role in Education	Meta-Analysis	Suggested AI significantly enhances learning and teaching processes.	[5]
Haenlein & Kaplan	2019	AI's Potential in Education	Theoretical Discussion	The research underscored the untapped capabilities of AI in democratising education.	[2]
Mduma et al.	2019	Student Dropout Prediction	Machine Learning	Utilised ML methodologies, including SVM, to predict student dropout.	[38]
Nicholas-Omoregbe et al.	2017	ICT Tools on Learning Outcomes	Empirical Study	The minimal impact on learning outcomes highlights a gap pointing to AI's potential role.	[41]

prediction to the exploration of AI's potential in democratising education. This table serves as a synthesised representation of the comprehensive analysis provided within the manuscript, focusing on the integration and impact of AI in ODL environments and the critical role of moderating elements such as gender and geographical differences.

Within the expansive landscape of AI's application in educational settings, methodologies span from empirical studies to theoretical discussions. Notably [1,2], lay the groundwork for understanding AI's broad potential, while empirical evidence from Ref. [28] directly links AI's application to enhanced student performance in ODL environments. However, the variance in methodologies and focus areas across these studies points to a critical gap: the need for a unified framework to accurately predict and assess AI's impact on academic performance in ODL settings. This comparative analysis underscores the recommendation for a process-based framework to address these disparities.

The methodologies in the literature encompass various approaches, including survey analysis, case studies, theoretical discussions, and empirical studies. Each methodology provides unique insights into AI's role in education but has limitations, particularly in predicting AI's impact on academic performance in ODL. For instance, while insightful for understanding perceptions and potential factors influencing AI adoption, survey analyses lack the predictive power of empirical methods. However, empirical methods often do not account for the broad range of variables that can influence AI effectiveness. This gap underscores the necessity for a comprehensive, process-based framework that integrates diverse methodological insights to accurately predict AI's impact on academic performance in ODL settings.

This systematic literature review was designed to pinpoint the factors influencing AI integration in the ODL and to examine its impact on student outcomes. Unlike previous reviews, this study delves into gender and regional disparities in AI's educational impact, recommending a process-based framework tailored to diverse educational settings. The method involved an exhaustive review of articles published between 2017 and 2023 from reputable databases, focusing on research on AI applications in education.

Recent studies have shown that while many studies have explored various aspects of AI in education, none have provided a comprehensive framework capable of predicting AI's impact across diverse settings, especially considering gender and regional disparities. This study's recommendation for a process-based framework is positioned to fill this gap by offering a structured approach to understanding and predicting the effects of AI adoption in ODL, making it a significant contribution to the field.

Table 2 underscores the diverse methodological landscape and the varying focus areas of existing research on AI in education. This diversity highlights the potential of AI to enhance educational outcomes significantly. However, the need for a process-based framework becomes evident to unify these disparate findings into a coherent predictive model for AI's impact on academic performance in ODL settings, considering gender and regional differences. Future research should aim to design and include comparative experiments that can validate the effectiveness of the recommended process-based framework. Such experiments could involve applying the framework to predict academic outcomes in ODL settings and comparing these predictions to actual results, thereby testing the framework's accuracy and adaptability. A structured taxonomy is introduced in the following section, transitioning from the detailed analysis and offering a clear comparative overview of AI techniques and their roles in ODL.

This literature review highlights the diverse methodologies employed to investigate the role of AI in education and identifies key areas requiring further exploration. This study employs a systematic literature review method, detailed in the subsequent section, to address these gaps by identifying the critical factors influencing AI integration in ODL and its effects on student outcomes.

3. Materials and methods

A systematic review was conducted between 2017 and 2023 to investigate the current state of research on predicting the effect of AI implementation on students' academic performance in ODL settings. The methodology for this systematic literature review was carried out following a robust protocol consistent with established processes [54]. This review focused on various aspects of AI incorporation in ODL environments. These included the factors prompting its integration, AI's effects on student's academic performance, the utility of machine learning in predicting this impact, and potential disparities regarding gender and geographical location concerning AI's effects on academic achievement in ODL settings.

The systematic review process was organised into four primary stages, as illustrated in Fig. 1.

I. **Identifying pertinent research:** This initial step involved an exhaustive search for studies relevant to the topics of interest.
II. **Screening process:** The titles and abstracts of the identified studies were scrutinised to exclude irrelevant research.
III. **Evaluation for eligibility:** The full texts of the remaining studies were meticulously assessed against the predetermined inclusion and exclusion criteria, focusing on their relevance to the research objectives. Specifically, studies that directly addressed AI's impact on academic performance in ODL settings were prioritised. Additionally, articles that provided robust

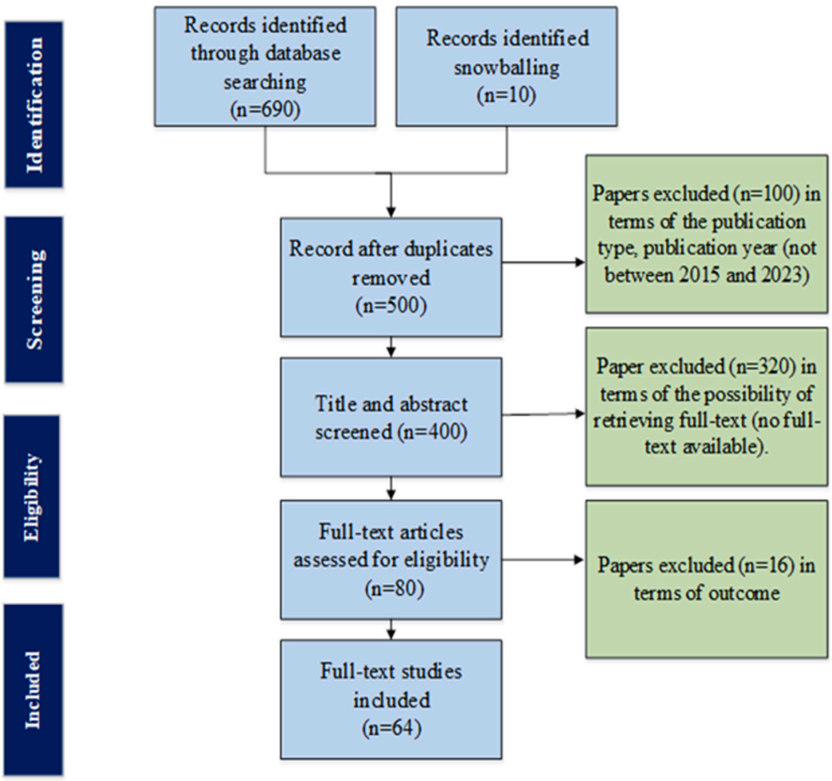

Fig. 1. The systematic reviews and meta-analysis (PRISMA) flowchart.

methodological frameworks, such as those employing machine learning for predictive analysis, were given particular attention. This rigorous selection process ensures that the included studies offer high-quality insights into the research questions posed.

IV. **Study inclusion and result synthesis:** The studies that met the criteria were included in the review, and their findings were synthesised to answer the research questions.

3.1. Database search

An exhaustive search was conducted using three major publisher databases, namely, Scopus, Google Scholar, and Web of Science, to identify empirical research on AI applications in education. The search was narrowed by applying filters to pinpoint empirical studies and peer-reviewed education and educational research articles published explicitly from 2017 to 2023. After an initial screening of the articles, a snowballing technique, as described by Ref. [55], was employed in the study to identify additional relevant articles. This method supplemented the initial findings, capturing articles not initially picked up through the search strings and ensuring a comprehensive review of the topic.

3.2. Identification of search terms

Based on the specific parameters of the bibliographic databases, search strategies were developed to best reflect the research questions. Keywords were selected under three main categories. First, keywords pertaining to artificial intelligence in education (AIEd) and specific AI applications were selected, including but not limited to "artificial intelligence," "AI," "machine learning," "intelligent tutoring system," "expert system," "personalised learning," "adaptive learning," "data mining," "learning analytics," "prediction model," "automated evaluation," "robot," "virtual agent," and "algorithm." Additionally, to address the research question on using the support vector machine approach, the term "support vector machine" was included.

Second, terms related to online distance learning were included to address the first research question. The keywords in this category were "online distance learning," "ODL," "e-learning," "distance education," and "online education." Finally, keywords associated with education and learner performance, such as "education," "learning," "course," "teaching," and "academic performance," were used. To further pinpoint studies addressing the last research question, keywords related to moderating factors, such as "gender differences" and "regional differences," were included.

The search was tailored to ensure the selection of the most pertinent articles to the research questions and the topics of AI adoption in ODL settings. By incorporating these search strategies, the aim is to identify the key factors driving AI adoption in ODL, determine the impact of AI adoption on students' academic performance, predict academic performance using the SVM approach, and understand how gender and regional differences can influence the effects of AI adoption on academic performance in ODL.

3.3. Search criteria

The search criteria were tailored to identify articles focusing on the impact of AI adoption in ODL settings on students' academic performance. Following the research objectives, specific inclusion and exclusion criteria were used (refer to Table 4).

3.4. The screening processes

The screening process involved the following steps.

I. Duplicate articles were excluded;
II. Title and abstract review for initial article removal, adhering to the inclusion and exclusion criteria;
III. Full-text analysis for further article elimination, following the established inclusion and exclusion criteria;
IV. Additional article identification using a snowballing approach in Scopus, Google Scholar, and Web of Science;
V. The data were extracted from the finalised set of selected articles.

Table 4
Inclusion and exclusion criteria.

Inclusion criteria	Exclusion criteria
1. Studies that are relevant to the research question	1. Research works not pertinent to the focal question of the study.
2. Publications included should be from peer-reviewed academic journals and proceedings of scholarly conferences.	2. Articles not peer-reviewed. Articles from book chapters, magazines, news, and posters are excluded
3. The studies should be reported in English	3. The studies not reported in English
4. Articles published between 2017 and 2023	4. Articles not published between 2017 and 2023
5. Full-text available	

3.5. Selection of data items

The focus was on outcomes directly related to the research objectives and questions. These included evaluating the effects of AI adoption on academic performance and engagement in open and distance learning contexts. This review aimed to understand the contextual factors influencing these outcomes, such as geographic location and gender-based differences in AI adoption. The systematic approach ensured that all results pertinent to these research dimensions were comprehensively included, offering a holistic view of AI's impact in educational settings.

3.6. Study risk of bias assessment

The risk of bias in the included studies was assessed using tailored criteria appropriate for this review's focus on artificial intelligence in open and distance learning. The assessment was independently conducted by two reviewers, ensuring objectivity and reliability. Discrepancies between their assessments were resolved through discussion or consultation with a third expert reviewer if needed. This process ensured a comprehensive and unbiased evaluation of each study's methodological quality.

The systematic literature review, as outlined in the methodology section, has yielded insightful information on AI's integration into ODL environments. The results section presents the findings, showcasing the range of impacts AI has on student learning outcomes and the methodologies driving these educational advancements.

4. Results and discussion

4.1. Summary of the findings

This exhaustive review provides a panoramic view of the swiftly expanding intersection between AI and education, further focusing on its role in ODL. At its core, the research is geared towards identifying determinants propelling AI adoption in ODL, assessing its impact on academic performance, and acknowledging the growing role of machine learning techniques such as SVM in forecasting academic outcomes [25,33,35,38–40].

4.1.1. Determinants of AI adoption in ODL

Distinctive aspects of ODL, such as alignment with institutional goals, comparative benefits, and preparedness for AI, are key factors driving its integration, as noted by Refs. [4,12,16]. Moreover, frameworks such as TAM, D&M, and UTAUT, recognised globally, significantly contribute to the understanding of AI adoption rates, as highlighted in studies by Refs. [20,25,56]. Additionally, factors such as user acceptance, access to technology, motivation, and self-efficacy have been identified as influential in this context, as validated by the research of [24,27].

4.1.2. Areas of AI application and AIEd research focus

AIEd research is primarily geared towards improving learning outcomes, easing teaching workloads, personalising learning experiences, and streamlining assessments [57,58]. AI applications often fall into four major domains: characterisation and forecasting, appraisal and examination, customisable systems and individualisation, and intelligent instructional systems, as described by Ref. [3].

4.1.3. Academic performance and interaction dynamics

AI enhances learner-educator interactions and positively impacts academic outcomes [3,5,6,58,59]. However, it is crucial to address risks such as overreliance on AI, AI-induced anxieties, and overstandardisation [26,37,59]. A robust framework balances these advantages and disadvantages [33,34,37].

4.1.4. Machine learning and prediction capabilities

This review highlights the efficacy of machine learning methodologies, particularly SVM, in forecasting academic results, thereby emphasising the symbiotic relationship between AI and education [60–62]. These methodologies are pivotal in transforming data into actionable insights, significantly improving the predictiveness and adaptability of educational models to diverse learner needs.

4.1.5. Moderating factors: gender and region

Finally, gender and regional disparities must be considered as significant moderating factors affecting the impact of AI on ODL [50–53]. Gender-based biases and regional variations related to technology infrastructure and cultural attitudes towards technology also require further investigation [10,63]. Further investigation into how gender and regional disparities affect the adoption and impact of AI in education is crucial. Future studies should aim to collect and analyse data that reflect these moderating factors, providing insights that could lead to more inclusive AI educational technologies.

This review proposes a multifaceted approach to understanding and integrating AI in ODL settings. It incorporates a complex interplay of driving factors, potential benefits, and challenges, along with the evolving role of machine learning in predictive analytics. Further research is crucial to dissect the gender and regional nuances that moderate the impact of AI adoption on ODL.

This review makes a significant contribution to the academic discourse by mapping the theoretical landscape of AI in ODL and highlighting critical gaps that need to be addressed. By identifying these gaps, this study sets a clear agenda for future research, particularly in developing process-based frameworks that can better predict and enhance AI's impact on academic performance. Such frameworks should prioritise inclusivity and adaptability, ensuring that AI-driven educational technologies cater to diverse student populations across various regions and socioeconomic backgrounds. By doing so, future research can help bridge the divide between the potential of AI in education and its practical implementation, fostering a more equitable and effective learning environment. The field can better understand and utilise AI's potential in transforming educational environments by moving towards empirical studies, thereby making theoretical contributions more actionable and aligned with practical outcomes.

4.1.6. Theoretical contributions and potential implications

While this review primarily synthesises existing theoretical and empirical studies, it importantly sets the groundwork for understanding how AI can be applied in ODL to improve educational outcomes. This review identifies critical AI adoption determinants and discusses their theoretical impact on learning environments. For instance, integrating AI can potentially enhance personalised learning experiences and improve academic performance, as suggested by the correlations drawn in the literature.

Given the current state of research, this review underscores the need for practical applications of these theoretical findings. Future empirical studies should test the predictions made by existing AI models within real-world ODL settings. Such research would provide the quantitative data necessary to validate the theories discussed and offer concrete examples of AI's impact on educational outcomes. The results reveal significant insights into the application and efficacy of AI in enhancing ODL experiences. In the following discussion, these findings are interpreted, considering the broader implications for pedagogical strategies, educational policy, and future research directions in AI-assisted learning.

4.2. Discussion of the results

This section delves into the implications of the findings and their alignment with existing theories and practices within AI in education, mainly focusing on ODL. The panoramic view of this review underscores a critical interconnection between AI advancements and educational methodologies, revealing a dynamic landscape influenced by technological, pedagogical, and socioeconomic factors.

I. **Interpreting the Determinants of AI Adoption in ODL:** The identified determinants of AI adoption, such as institutional alignment and technological readiness, reflect a broader consensus on the prerequisites for successful AI integration in educational settings. The emphasis on models such as TAM, D&M, and UTAUT in facilitating understanding of AI adoption underscores the importance of theoretical frameworks in predicting and enhancing technology acceptance in ODL contexts. Compared to existing studies, this review provides a comprehensive synthesis that integrates diverse determinants across different educational frameworks, positioning this research as a unifying overview that bridges multiple theoretical insights.
II. **Evaluating AI's Role in Academic Performance:** The positive impact of AI on academic performance, as highlighted through SVM's predictive capabilities, showcases AI's potential in personalising learning and improving outcomes. However, the discussion extends to acknowledging the nuanced challenges accompanying AI integration, such as potential overreliance and the risk of standardisation. This balanced view advocates a cautious yet optimistic approach to leveraging AI in education, distinguishing this review from others by its comprehensive evaluation of benefits and risks, often not covered in tandem in the literature.
III. **Addressing Moderating Factors:** The emphasis on gender and regional disparities as moderating factors sheds light on the equity dimensions of AI in education. This discussion aligns with a growing body of research advocating for inclusive and equitable AIEd solutions that cater to diverse learner populations. It also highlights the need for future research to explore these disparities further and develop strategies to mitigate them. This review extends the current discussions by providing a deeper analysis of how such factors can be integrated into AI implementations in educational settings, an area often overlooked in similar studies.
IV. **Synthesising AIEd Research Focus and Application Areas:** By categorising AI applications and research focuses, the review maps the current state of AIEd and identifies areas ripe for innovation. This synthesis provides a foundation for future explorations into how AI can further streamline educational processes, enhance learning experiences, and address pedagogical challenges. The systematic approach to categorising these applications sets this review apart from the literature by offering a clear and structured overview of AI's potential across different educational facets.

This discussion bridges the gap between theoretical understanding and practical applications of AI in ODL by synthesising the findings from various studies. It underscores the multifaceted impact of AI adoption, highlighting both the opportunities for enhancing educational outcomes and the challenges, such as the potential for over-reliance on technology and the risk of exacerbating existing inequalities. It highlights the complexity of AI adoption and its multifaceted impact on education, urging continued exploration into how AI can be most effectively and equitably integrated into educational practices.

Towards the conclusion of the systematic review, it becomes evident that despite the extensive exploration of AI's potential to enhance educational outcomes, a significant gap remains in the ability to predict these impacts systematically and inclusively. This observation leads to the recommendation of developing a process-based framework designed to do the following.

I. **Enhanced Predictive Capabilities:** A unified methodological approach is paramount for accurately predicting the impact of AI adoption on student academic performance across diverse educational contexts and demographics.

II. **Incorporate Inclusivity and Equity:** The findings underscore the importance of moderating factors such as gender and geographical disparities in the impact of AI. A process-based framework that integrates these considerations could pave the way for developing more equitable and inclusive AI educational technologies.
III. **Comprehensive Guidance for AI Integration:** The recommended framework offers actionable insights for educators, policymakers, and researchers, guiding the thoughtful and effective incorporation of AI technologies in education and emphasising their full potential while navigating associated challenges.

This systematic literature review synthesises a broad spectrum of research, identifying critical gaps and opportunities rather than directly comparing individual studies or existing frameworks. This methodological choice is deliberate, aiming to highlight the collective insights and emergent needs identified through comprehensive analysis. By focusing on the recommendation for a future process-based framework, the necessity of addressing these gaps with a novel, unified approach that can cater to the complex dynamics of AI in education is highlighted. This forward-looking perspective is essential for laying the groundwork for subsequent empirical research and development in this evolving field. Next, AI models for predicting academic performance in ODL settings are compared, building on the insights from the discussion. This comparison aims to shed light on the efficacy of different AI approaches in enhancing educational outcomes.

4.3. AI model comparison for ODL academic performance prediction

This section evaluates the effectiveness of decision trees, random forests, neural networks, and SVMs in predicting academic performance in ODL.

I. **Decision trees** offer simplicity and interpretability but may overfit complex datasets.
II. **RF** improves accuracy and combats overfitting by leveraging multiple decision trees suitable for extensive data but computationally intensive.
III. **Neural networks** excel in modelling complex patterns with high accuracy but are computationally demanding and less interpretable.
IV. SVMs balance accuracy and interpretability, efficiently handling high-dimensional data but requiring precise parameter tuning.

The models vary in predictive accuracy, computational demand, and interpretability (see Table 5). Decision trees and SVMs are more interpretable and easier to understand. At the same time, neural networks and random forests offer superior accuracy but at the expense of increased computational complexity and reduced interpretability. Choosing a suitable AI model involves balancing accuracy, resource availability, and the need for transparency, guiding future research towards optimised AI applications in education.

This comparative analysis underscores the importance of selecting an AI model that aligns with the specific needs of ODL environments, considering factors such as dataset complexity, resource availability, and the necessity for model transparency. Future research should further explore the integration and optimisation of these models within the ODL context to enhance predictive analytics in education. The analytical lens is broadened after exploring AI models' comparative strengths and limitations in predicting ODL academic performance. The following meta-analysis synthesises findings across studies to identify overarching trends and implications for the role of AI in ODL.

4.4. Meta-analysis

This research encompasses a total of sixty-four scholarly works. These chosen publications provide an extensive exploration of several themes, such as the driving forces behind the adoption of AI, the effects of integrating AI on academic outcomes in ODL environments, the application of machine learning algorithms in forecasting student academic achievements, and the influence of gender and regional disparities as moderating factors. The selection criterion was primarily based on these articles' significant contributions to elucidating these facets, offering invaluable perspectives and findings on AI adoption and its subsequent implications for academic performance in ODL.

This review revealed that machine learning methods were the predominant approach employed in 26.56 % of the studies. This considerable usage underscores the keen interest within the field in leveraging machine learning techniques, indicating a strong likelihood of their continued application in future research. Classical statistical methods were utilised in 26.56 % of the studies. Despite not being cutting-edge, these methods remain essential in numerous research investigations, such as machine learning. A total of 3.13 % of the studies utilised hybrid methods, suggesting their relatively niche application. The most extensive category, nonempirical

Table 5
Comparison of AI models.

Model	Accuracy	Efficiency	Interpretability
Decision Trees	Moderate	High	High
Random Forest	High	Moderate	Moderate
Neural Networks	Very High	Low	Low
SVM	High	High	High

methods, comprised 43.75 % of the studies. These methods encompass theoretical analyses, literature reviews, and other non-data-driven approaches. The methodology distribution within the included studies is presented in Fig. 2, which depicts a graphical representation of the methodologies applied across the selected studies, providing a visual summary of the various research methods employed in these investigations.

The temporal distribution of the reviewed articles, as illustrated in Fig. 3, provides significant insights into the evolutionary trajectory of the research domain. The analysis included 64 articles from 2017 to 2023 (see Table 6). An overall upward trend in annual publications is observed over this duration. In 2017, four articles were considered. After slightly decreasing to three articles in 2018, the number returned to four in 2019. A significant increase in research output occurred in 2020, with eight articles, reaching a peak in 2021 with seventeen publications. This trend continued into 2022, when sixteen articles were considered. However, in 2023, a mild decline to twelve articles was observed. This reduction could either be due to the ongoing nature of the year at the time of this review or possibly indicative of a shift in publication patterns. The temporal distribution has attracted increasing interest in the research area, underscored by the increasing annual volume of publications. Moreover, there is intensifying interest among the research community in the topics addressed by these articles, culminating in a flourishing body of published research.

The year-over-year increase in publication volume speaks to this domain's burgeoning relevance and significance, emphasising the continued need for research to continue up-to-date with its swift advancement. Thus, the findings of this review are not only timely but also distinctly relevant to the contemporaneous status of the field.

This section analyses the cited journals based on their SCImago Journal Rank (SJR) and impact factor. Both are widely used to gauge the significance of academic journals. The key insights include.

I. **Journal Selection:** 'Computers & Education' has emerged as a popular choice, emphasising its relevance in the field.
II. **Journal Metrics:** 'The Journal of Innovation & Knowledge' has the highest SJR (2.649) and impact factor (20.310), indicating its substantial influence. Figs. 4–5 graphically represent this alongside other top journals.
III. **Metric variation:** A broad range of SJR and impact factor values across different journals suggests varying degrees of influence and reach.
IV. **Unspecified Metrics:** Some journals lack SJR or impact factor values, complicating their assessment based solely on these metrics. However, it is vital to remember that journal evaluation should consider aspects such as journal scope, research quality, and topic relevance.

This meta-analysis provides an in-depth evaluation of AI deployment in ODLs, showing the methodologies adopted, the temporal growth in research output, and the dissemination of findings across critical academic journals. The limitations of this study are addressed next, highlighting the necessity of further research to enrich and expand upon the understanding of the educational impact of AI.

4.5. Limitations of the study

This study, while comprehensive, acknowledges its limitations, particularly in the direct design and testing of the proposed process-based framework. The study's focus on recommending rather than implementing a framework means that its practical effectiveness remains to be validated through empirical research. Moreover, this systematic literature review may not encompass all relevant studies, especially those published outside the selected databases or in languages other than English. These limitations highlight the necessity for ongoing research to refine and empirically test the recommended framework, ensuring that it effectively addresses the identified gaps in the literature on AI's impact on academic performance in ODL settings.

In this systematic review, a qualitative synthesis approach was necessary due to the diverse methodologies and outcome measures used in the reviewed studies, limiting the feasibility of a quantitative synthesis and calculating effect measures such as risk ratios or mean differences. While this precluded quantitative aggregation, it facilitated an in-depth exploration of themes and trends. Reporting biases were assessed by critically examining study protocols and reports to identify selective outcome reporting. However, quantitative

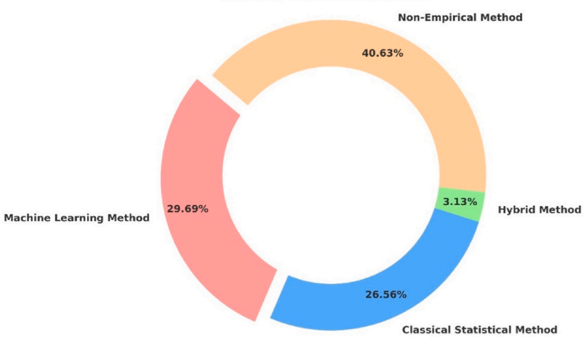

Fig. 2. Percentage distribution of the methods used in the studies reviewed.

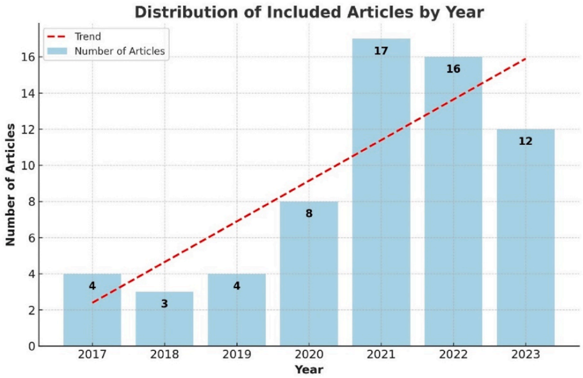

Fig. 3. Distribution of the articles included in the study by year.

methods such as funnel plot analysis were not used due to the lack of quantitative data. Consequently, the conventional GRADE approach for assessing evidence certainty was not applicable, leading to a focus on narrative analysis and recognition of the limitations and variability inherent in the study designs and reported outcomes.

While the study comprehensively explored the role of AI in enhancing ODL, it also highlighted critical limitations, mainly focusing on theoretical recommendations for practical application and the potential exclusion of relevant studies outside the selected databases. These constraints underscore the pressing need for future research to design, empirically validate, and refine the recommended framework. Such research would test the framework's practical applicability and expand the understanding of AI's transformative potential in ODL. As the transition to concluding remarks and recommendations occurs, these considerations inform the proposed steps forward, aligning with the ultimate goal of maximising AI's benefits for educational outcomes in ODL environments.

5. Conclusion and recommendations

This comprehensive examination of the relevant academic literature highlights the dual aspects of integrating AI into educational settings. AI has transformative potential for reshaping multiple aspects of teaching and learning, positioning itself as a crucial agent of change in the educational landscape. On the other hand, potential downsides and negative repercussions must also be considered. This dichotomy underlines the critical need for a solid process framework capable of forecasting the consequences of AI incorporation for student academic performance, especially within ODL settings. The importance of developing and refining such a framework is integral to effectively leveraging the beneficial potential of AI while concurrently mitigating potential hazards. With a balanced, considerate approach, it is possible to tap into the transformative power of AI within education.

The evaluation of various research methodologies throughout this review has emphasised the robust capabilities of machine learning strategies, notably SVM, in forecasting academic results. This revelation accentuates the growing intersection of AI and education, with machine learning techniques emerging as influential tools within educational research. The studies reviewed within this discourse have also illuminated critical motivators propelling the adoption of AI within distance learning contexts. They underscore its broad implications for student outcomes, suggesting that AI can enrich the learning experience and potentially bolster educational attainment. It is suggested that the key constructs from globally recognised theories such as TAM, D&M, and UTAUT can be innovatively merged with factors that are uniquely relevant to the ODL setting. This approach will create a comprehensive framework designed to encapsulate the broad spectrum of experiences pertinent to ODL contexts.

Moreover, these investigations underscore AI's potential to enhance interactions between learners and educators within digital arenas. This aspect is particularly noteworthy in online and remote education, where AI could facilitate efficacious pedagogical practices. Additionally, exploring intermediate factors such as gender and geographic disparities provides a deeper understanding of the complex dynamics of integrating AI within the educational sphere. This nuanced understanding assists in achieving a more holistic appreciation of AI's possible positive and negative repercussions on the educational sector.

In conclusion, this review underscores the growing importance of AI in transforming educational contexts, particularly within ODL environments. It also emphasises the prospective influences of AI on student outcomes, urging the need for ongoing research to develop frameworks that can predict and optimise these impacts effectively. This analysis aids in understanding the determinants that drive the effective incorporation of AI into ODL systems. This study illuminates the possible effects of AI integration on student academic outcomes in ODL settings. Considering AI's transformative capabilities in education, coupled with the distinct challenges presented by ODL, there is a pressing need for a process-based framework that can predict the consequences of AI adoption in these settings. This review provides insights that pave the way for the design and implementation of such a predictive framework, ensuring that AI is leveraged effectively to enhance student outcomes in ODL contexts.

5.1. Recommendations

Based on the systematic literature review, the following recommendations are made.

Table 6
Ranking of studies and published journals.

S/N	Articles	Journal Name	Scopus-SCImago Journal Rank (SJR)	Impact factor
2017				
1	[4]	Online Learning	1.417	5.030
2	[41]	Turkish Online Journal of Distance Education-TOJDE	0.449	2.420
3	[44]	Computers & Education	3.676	11.182
4	[59]	Research and Practice in Technology Enhanced Learning.	0.654	3.440
2018				
5	[19]	Information Development	0.560	2.079
6	[28]	Proceedings of the 3rd International Conference on Multimedia Systems and Signal Processing	N/A	N/A
7	[55]	PLoS ONE	0.885	3.750
2019				
8	[2]	California Management Review	3.793	11.678
9	[27]	Journal of Baltic Science Education	0.478	1.480
10	[38]	Data Science Journal	1.026	2.780
11	[50]	International Learning Analytics & Knowledge Conference (LAK19)	N/A	N/A
2020				
12	[3]	Computers & Education	3.682	15.58
13	[5]	Computers & Education	3.682	15.58
14	[20]	Proceedings of the 53rd Hawaii International Conference on System Sciences	N/A	N/A
15	[36]	Heliyon	0.609	4.450
16	[39]	Computers & Education	3.682	15.580
17	[43]	Computers & Education	3.682	15.58
18	[58]	Creative Education	N/A	0.500
19	[63]	Benchmarking	1.185	7.970
2021				
20	[1]	Educational Technology & Society	1.049	5.080
21	[6]	International Journal of Educational Technology in Higher Education,	2.051	10.420
22	[7]	In Lecture Notes in Computer Science	0.320	1.270
23	[15]	Academic Journal of Interdisciplinary Studies	0.183	0.810
24	[16]	Sustainability	0.664	4.390
25	[18]	IEEE Access	0.930	3.476
26	[22]	PLoS ONE	0.885	3.750
27	[29]	Proceedings of the AAAI Conference on Artificial Intelligence	0.630	5.000
28	[34]	Smart Learning Environments	0.967	6.310
29	[37]	Educational Technology & Society	1.049	5.080
30	[40]	PLoS ONE	0.885	3.750
31	[45]	Journal of Interconnection Networks	0.207	0.550
32	[46]	TEM Journal	0.231	1.210
33	[53]	NetHope	N/A	N/A
34	[56]	Sustainability	0.664	4.390
35	[57]	AI And Ethics	N/A	N/A
36	[60]	International Conference on Computer & Information Sciences (ICCOINS)	N/A	N/A
2022				
37	[9]	International Journal of Academic Research in Progressive Education and Development	N/A	N/A
38	[10]	Computer and Information Science	0.924	6.053
S/N	Articles	Journal Name	Scopus-SCImago Journal Rank (SJR)	Impact factor
39	[11]	Mathematical Problems in Engineering.	0.355	2.100
40	[12]	In Tenth Pan-Commonwealth Forum on Open Learning.	N/A	N/A
41	[13]	Mathematical Problems in Engineering	0.355	2.100
42	[21]	Electronics	0.148	0.530
43	[23]	Education and Information Technologies.	1.249	7.650
44	[24]	A Journal of Management Research	0.567	3.460
45	[25]	Telematics and Informatics	1.878	10.090
46	[30]	2022 17th Iberian Conference on Information Systems and Technologies (CISTI).	0.146	0.493
47	[32]	Frontiers in Psychiatry	1.222	4.520
48	[35]	Artificial Intelligence Review	2.490	15.010
49	[42]	Proceedings of International Conference on Information Systems and Emerging Technologies (ICISET) and International Conference on Data Science, Machine Learning and Artificial Intelligence (DSMLAI)	N/A	1.000
50	[48]	Jurnal Pendidikan: Teori, Penelitian, Dan Pengembangan	N/A	N/A
51	[51]	Humanities and Social Sciences Communications	0.705	3.810
52	[61]	International Journal of Information and Education Technology	0.243	1.690
2023				
53	[8]	Indian Scientific Journal of Research in Engineering and Management	N/A	N/A
54	[14]	Qeios.	N/A	N/A

(*continued on next page*)

Table 6 (*continued*)

S/N	Articles	Journal Name	Scopus-SCImago Journal Rank (SJR)	Impact factor
55	[17]	E3S Web of Conferences	0.180	0.380
56	[26]	Journal of Artificial Intelligence Machine Learning and Neural Network	N/A	N/A
57	[31]	Journal of Innovation & Knowledge	2.649	20.310
58	[33]	International Journal of Educational Technology in Higher Education	2.051	10.420
59	[47]	International Journal of Artificial Intelligence in Education.	1.110	4.980
60	[49]	Behav Sci (Basel)	0.597	2.980
61	[52]	Journal of University Teaching and Learning Practice	0.488	2.030
62	[54]	Computing	0.824	4.331
63	[62]	In Advances in medical education, research, and ethics (AMERE)	N/A	N/A
64	[64]	International Journal of Computational Intelligence Systems	0.550	2.900

Fig. 4. The top 10 journals by impact factor.

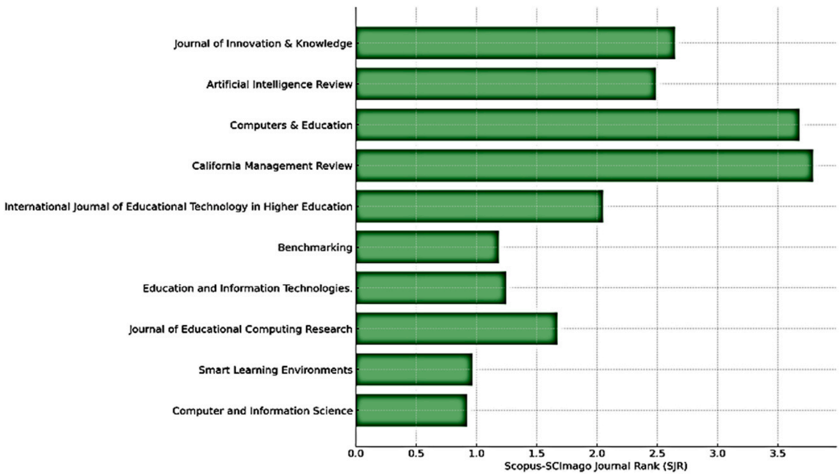

Fig. 5. The top 10 journals by SJR

I. **Development of a process-based framework:** The study recommends developing a process-based framework grounded in both educational theories and advanced machine learning techniques to accurately predict and enhance the impact of AI adoption on academic achievement in ODL settings. This framework should be continuously refined through empirical testing and adaptation to ensure its effectiveness across diverse educational environments.

II. **Integration of state-of-the-art machine learning algorithms:** The recommended process-based framework should be algorithm-independent, allowing for the future incorporation of advanced machine learning algorithms such as random forest and whale optimisation, which have shown success in other fields [49,64].
III. **Integrate Globally Recognised Theories:** When formulating the framework's structure, it is advisable to integrate essential components derived from internationally recognised theories, such as the TAM, D&M, and the UTAUT. This approach will establish a robust theoretical foundation for the framework.
IV. **Tailor to the ODL Setting:** The designed framework should also factor in elements uniquely relevant to the ODL context. This adaptation will lead to a comprehensive framework that captures a broad spectrum of experiences relevant to ODL settings.
V. **Empirical validation of the framework:** The recommendation of a process-based framework opens several avenues for future research. The following steps involve the empirical design and testing of the framework to assess its predictive accuracy and adaptability across different ODL contexts. Additionally, future research should explore the framework's applicability to emerging AI technologies and methodologies in education, ensuring that it remains relevant and effective in predicting AI's impact on academic performance. Moreover, further investigation into gender and regional disparities in AI's educational impact is crucial to ensure that the framework's recommendations cater to diverse student populations, promoting inclusivity and equity in ODL environments.

By addressing these suggestions, future research can significantly contribute to advancing the understanding of AI's role in enhancing academic outcomes in ODL, ensuring that AI adoption is leveraged effectively and equitably across diverse educational settings. By addressing these recommendations, this systematic literature review will contribute to developing a more refined and accurate approach to predicting the impact of AI adoption on students' academic performance in ODL settings.

This study clarifies the call to develop a process-based framework to predict the impact of AI adoption on students' academic performance in ODL settings. This recommendation is grounded in the identified research gaps and the critical need for a holistic, predictive model that accounts for the complex interplay of factors influencing educational outcomes in the age of AI. Future research endeavours are encouraged to address this challenge by crafting a framework that harnesses the full potential of AI to enhance learning experiences while addressing the nuances of equity and inclusivity. By elucidating the need for such a framework and emphasising its importance for advancing AI in education, the goal is to inspire future research that can transform educational practices and outcomes through informed and thoughtful AI integration.

CRediT authorship contribution statement

M.D. Adewale: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **A. Azeta:** Writing – review & editing, Supervision, Investigation, Conceptualization. **A. Abayomi-Alli:** Writing – review & editing, Validation, Supervision, Investigation. **A. Sambo-Magaji:** Writing – review & editing, Validation, Supervision, Investigation.

Declarations

This research involved no human participants, data, tissues, or animals; therefore, no ethical approval or informed consent was needed. This study followed applicable guidelines and regulations and adhered to academic integrity principles. No conflicts of interest exist. The data were obtained from established academic databases, and this manuscript is not under consideration for publication elsewhere. The findings and conclusions are those of the authors and do not represent our institutions or funders.

Data availability statement

All data for this systematic review were sourced from public academic databases, including Scopus, Google Scholar, and Web of Science. Any additional inquiries should be directed to the corresponding author.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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